Introduction

Pore types in carbonate rocks are highly variable due to the wide range of depositional environments and the subsequent overprints resulting from compaction, diagenesis and tectonic deformation. To optimize production from carbonate reservoirs a better understanding of the relationship between the pore system and petrophysical properties is needed (e.g., Norbirsrath et al. 2015). We are currently developing a toolset, workflow and deep learning software package that will tackle this problem.

The main objectives of the project are:

1. Image, quantify and visualize the connected and unconnected matrix and fracture (micro-) pores in carbonate reservoir rocks at multiple scales.
2. Develop machine learning algorithms to automatically segment and classify these pores from the image data.
3. Design a workflow to derive petrophysical properties from classified and quantified pore data.

Pore networks in carbonates can be much more complex than in clastic sediments. There are no tools on the market able to automatically recognize and classify these pores. Especially quantifying the connectivity of pores in matrix and fractures represents a major challenge in the evaluation of carbonate reservoirs. We developed a Liquid Metal Injection (LMI) technique combined with Broad Ion Beam – Scanning Electron Microscopy (BIB-SEM) to visualize connected and unconnected pores in large 2D images; the latter are not part of the effective pore network and do not contribute to flow (Klaver et al. 2017).

The workflow includes high quality pore imaging and fast, automated segmentation. Pores are imaged by automated optical and scanning electron microscopy on high quality ion-polished surfaces. The machine learning algorithms will first learn to differentiate pores from rock. Subsequently, by training the algorithms with a combination of unsupervised and expert knowledge-based classification, we aim to automatically classify fracture and matrix pores in the core samples.

The semi-automatic analysis tool is fast, and computer controlled, it therefore yields a significant reduction of man-hours. Because the tool is unbiased, it will allow better comparison of carbonate rocks from various fields. The output of the tool will speed-up the rock typing process and the integration with petrophysical logs leading to more accurate geological reservoir models. Tangible improvement will be achieved on:
- Degree of confidence in the distribution and saturation of hydrocarbons and water
- De-risking the volumes and recoverability of the volumes
- A better description of reservoir rock quality and the link to low and high perm zones
- Productibility of the reservoir and possibly guide or improve the field development plan

The tool could also work on cuttings, thereby minimizing the need of taking cores, and significantly reducing costs. The knowledge-based pore classification may also be applied to analyse other rock types.

This contribution complements the gap in visualizing, quantifying, and classifying the pore space from the nano- to macroscale. Additionally, the first results of the automated pore segmentation and classification using deep learning will be presented.

Methods

Ultra-thin sections of each sample are imaged using the unique Virtual Petrography (ViP). The ViP is a fully automated petrographic microscope, which captures entire thin sections at high resolution (e.g. 45,000 x 30,000-pixel image maps for a single thin section of 3 x 2 cm) in a combined seamless dataset. Each dataset contains the parallel-polarized (PPOL layer) imagery as well as the extinction behaviour of each pixel under rotating crossed polarized (INTERPOL layer) light, including information about crystal birefringence and orientation and the presence of pores (Virgo et al. 2016,
Representative and typical sub-samples will be selected for Broad Ion Beam – Scanning Electron Microscopy (BIB-SEM) analyses based on the texture and porosity derived from CT and ViP investigations. High-quality damage-free cross sections will be prepared by BIB milling and imaged using a SEM. In the SEM, high-resolution image maps will be acquired by scanning hundreds of images using secondary and backscattered electron (SE and BSE, respectively) detectors and large maps (ca. 10,000 x 10,000-pixel map) of regions of interest or representative areas regarding the microporosity will be produced. Pore space will initially be segmented from image maps, which enables fast segmentation and quality control (Jiang et al. 2015). This quality-controlled dataset of over 10,000 pores in each sample is crucial as a ground truth for successful training of the deep learning algorithms.

Selected subsamples will be analysed using Liquid Metal Injection (LMI) method followed by BIB-SEM for pore connectivity analyses (Klaver et al. 2017). Briefly, a sample of about 1 cm³ is placed in a pressure cell with a low melting point alloy and heated to 80˚C until the alloy is molten. Then, pressure is increased stepwise up to a maximum of 400 MPa (equivalent to a pore throat diameter of 3 nm), similar to Mercury Intrusion Porosimetry (MIP). After cooling and solidification of the alloy under pressure, the sample is cut, BIB polished and subsequently imaged in the SEM. The great advantage of LMI-BIB-SEM compared to MIP is that the intrusion can be measured by subsequent visualization of the pores which were filled at the increasing injection pressures. This differentiates connected and unconnected porosity at different pore throat sizes (and thus gives key information on 3D pore networks using large, representative 2D images), highlights fracture networks over a relatively large area and reveals injection related artefacts. The LMI machine can accurately measure the intrusion volume with increasing pressure. This data will provide the full capillary entry curve (comparable to MIP), together with information on the percolation process down to a few nm pore throats, all without the use of Mercury.

State-of-the-Art deep learning is tailored and applied to achieve an integrated, automated pore segmentation and classification for all three image types: Macroporosity from ViP, Microporosity from BIB-SEM, and pore connectivity from LMI-BIB-SEM.

Preliminary results

Figure 1 shows a detail of the Desert Pink Limestone with the preliminary Deep Learning result of the PPOL pore segmentation. To investigate the microporosity we selected sub-samples based on the thin sections which we then imaged in the SEM. The high-resolution maps of the microstructure selected on the BIB cross-section have visible porosities around 7% for this sample of the Desert Pink limestone (Figure 2). The major part of this pore space is in the range of 1 to 10 µm in circular equivalent pore diameter.

Regarding the LMI-BIB-SEM investigations, the Desert Pink limestone shows at relatively low pressure of 2 bar a significant filling of the largest moldic pores with the metal. With increasing pressure more moldic pores get filled (Figure 3). At approximately 14 bar virtually all moldic pores are filled with the WM, however, the interparticle micropores between the cement and grains remain unreached by the metal. At a maximum pressure of 4000 bar, all the pore space is filled with WM, including the interparticle micropores.

Conclusions

Based on the current investigations it is clear that microporosity represents a large part of the porosity, and thus only visible in the SEM. As a simple check, the sum of the visible porosities compares well with the bulk porosities. And the results from the liquid metal injected samples are consistent with the mercury intrusion porosimetry. These outcomes provide a first batch of high-quality pore data for...
training the deep learning models which already show promising results on a relatively limited amount of data.

Figure 1 PPOL image of Desert Pink Limestone with manual pore segmentation in red and Deep Learning result in green polygons.

Figure 2 BIB cross-section of the Desert Pink Limestone, with the segmented microporosity in green polygons.
Figure 2 LMI-BIB-SEM overview images of the Desert Pink Limestone injected at various pressures indicated by the arrows. The diagram in upper left shows the mercury intrusion curve as a blue line and the LMI intrusion pressures as yellow bars.

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References

Jiang, M., Klaver, J., Schmatz, J. and Urai, J. L. [2015] Cryogenic Broad Ion Beam milling (BIB) and Scanning Electron Microscopy (SEM) to image pore morphology and fluid contacts in hydrocarbon reservoir rocks. Acta Stereologica, Proceedings of the 14th International Congress for Stereology and Image Analysis, 6-10 July 2015, Liège (Belgium), ISSN 0351-580X.


